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Original Article

AI-Driven Rice Leaf Disease Detection Leveraging Texture-Feature Fusion and Low-Dimensional Feature Spaces

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Abstract - *Rice leaf diseases pose a big threat to crop production in the world, and hence the importance of early and proper identification of the diseases to ensure a significant contribution in Fusion. The manual inspection is lengthy, biased, and not very uniform in the large farmlands. The paper introduces an AI-based framework of rice leaf disease determination, combining texture-feature Fusion with low-dimensional feature space maximization to improve the level of classification at the feature dimension. Multi-scale texture patterns were extracted by the system based on Gray-Level Co-occurrence Matrices (GLCM), Local Binary Patterns (LBP), and Gabor; they are combined with color-gradient descriptors to compose a hybrid feature single feature vector. Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) are used to reduce dimensions to a smaller and more discriminative space of features that can be used in lightweight models. Evaluated on standard rice leaf disease data, it has been demonstrated that the fused features are more accurate than training and validation, differences in illumination, and damage to some parts of the leaf. The findings show significant enhancements in the detection efficacy, especially of the early symptoms. In real life, practical constraints are that it requires varying and region-specific data, extreme light sensitivity when used in real fields, and the problem of a confusion matrix for rice leaf disease detection. The accuracy comparison and performance curve efforts should aim to deploy edges in real-time, add hyperspectral cues, and domain-generalization adaptively to make the model effective in various ecological regimes and rice varieties.*

Keywords - *Crop Monitoring, Rice Leaf Disease Detection, Texture Feature Fusion, Low-Dimensional Feature Spaces, PCA, LDA, Computer Vision In Agriculture, AI-Based.*

1. Introduction

Rice is a type of food crop that is highly significant in terms of maintaining world food security, as it is the major dietary crop for over half of the planet. Stable rice production is thus a strategic agricultural agenda for most emerging and developing economies. Nevertheless, rice crop is continually attacked by a greater number of diseases, which are blast, bacterial blight, brown spot, sheath rot, tango, and a variety of fungal conditions, which can lead to extreme loss of yield in rice crop. Such diseases tend to proliferate as fast because of the good climatic conditions, and early identification of such diseases is an essential need for proper management of crops [13]. The traditional method of identifying diseases by farmers is visual inspection, which is time-consuming, labor-intensive, and subjective in large farming areas. Due to the movement towards smart and precision agriculture methods, there has been a growing demand for automated, reliable, and scalable approaches for identifying rice diseases at the correct stage of occurrence. Computer Vision (AI) has attracted much interest due to the potential for automating disease detection in crops. CNNs and generally deep learning models have demonstrated very promising results in the process of classifying across different agricultural data. Their capability in learning hierarchical features automatically from the raw images avoids the necessity to engineer features using manual means. These models, however, are greatly limited since they need large volumes of labeled data to be trained, and they consume significant computational power and tend not to generalize across real-life variations like changes in lighting, occlusions, and different backgrounds. Such deep learning models cannot be put into practical use in the field, especially by smallholder farming communities that do not have high-performance computing facilities.

Researchers are going back to the strength of classical machine learning methods with handcrafted features in a bid to tackle these drawbacks. Among them, the textural descriptors are the key ones since the rice leaf diseases may be associated with irregular patterns, lesions, spots, streaks, or discoloration- the symptoms that are inherently textural in nature. Common texture measurement techniques include Gray-Level Co-occurrence Matrix (GLCM), Local Binary Patterns (LBP), and Gabor filters, as they are able to estimate the relationship of pixel intensity, micro-pattern structure, and multi-directional frequency responses. Each of the descriptors is considered informative, but when a single texture descriptor is used, it is likely that they are incomplete. There are those diseases that come out with fine-grained textures and others that are coarse, global discoloration, or any specific distortions of structure. This implies that no individual characterization can be fully used in defining a disease [1].

The second significant problem is due to the high dimension of the fused feature vectors. Characteristics obtained by more than one texture measure and color dimension are likely to be dimensional and over-representative, making them costlier to compute and lowering the efficiency of the classifier. High-dimensional data also promotes overfitting, particularly when the amount of data used to train is small. Thus, dimensionality reduction while preserving the discriminative properties is essential to the development of an effective and implementable disease detector model [9].

The given study attempts to solve these issues through the creation of an AI-based rice leaf disease detection infrastructure that utilizes the Fusion of texture features with the optimization of a low-dimensional feature space. The idea behind the core is to derive a series of descriptors representing the texture and combine the series into a hybrid feature space and utilize dimensionality reduction methods like Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) to produce a small but highly discriminative feature space. This small set of feature dimensions is then processed by easily trained lightweight classifiers, which can operate with high precision at a significantly reduced computational price relative to deep learning networks [10].

This strategy is quite consistent with the practical requirements of agro applications, where the models should be correct, strong, interpretable, and inexpensive to compute. The system is a fusion of the texture features in that it records multi-scale, multi-orientation, and multi-level structural changes typical of rice diseases. PCA filters out redundancy, which promotes gene rationalization in different fields of operation, whereas LDA boosts the ability to create a distance between the classes, which are visually similar to each other. This hybrid framework yields good results with limited training data, unlike deep learning models that demand thousands of samples, which is why it can be deployed in rural areas. Also, the approach to be proposed will help fill the gap between the research-based solutions and agricultural needs in the real world [3]. The majority of current AI models are trained in controlled settings where there is even lighting and clean surfaces, which are not a realistic setup of farming conditions. Conversely, the system suggested is resistant to changes in light, the position of leaves, noise in the image, and the partiality of seeing the symptoms of the disease-this issue is typically observed in the actual field of acquiring images [8]. Moreover, the application of low-dimensional feature spaces makes it suitable for mobile, drone-based, and edge-device applications where computational capabilities are small.

The other important factor is interpretability rather than accuracy. The classical descriptors of texture include explicit visual information and quantifiable statistical information, and it is less difficult to understand why the model considers a leaf diseased. This is most especially applicable in the case of decision-support systems, where explainability may enhance user trust and adoption of explainable systems, especially among farmers and agricultural extension officers.

Lastly, raising the question of scalable and interpretable multi-scale disease detection without involving complex deep learning networks, the proposed system was able to prove that comprehensive disease detection can be achieved effectively and at scale. This publication is relevant to precision agriculture because it provides a viable solution that balances precision, efficiency, and practicality in monitoring rice disease [11].

2. Related Study

Innovations in detecting rice disease have gone a long way in the last decade to leave behind the manual way of detection through visual means and move towards automated visual assessments through computers. The available literature is largely divided into four broad categories, which are: classical methods of machine learning that work with handcrafted features, deep learning-based methods, spectral and sensor-based imaging methods, and the hybrid methods that combine more than one feature extraction method [15]. All the categories bring crucial information on the design of automated systems in the detection of agricultural diseases, but there are still quite a few gaps that need to be filled, especially in terms of computational efficiency, field variability, and interpretability.

In 2025, S.-E. Marieme et al. [12] introduced the initial methods mainly used handcrafted features like color histogram, shape descriptions, and statistical texture measures in disease characterization on rice leaves. Such techniques usually relied on classical classifiers such as Support Vector Machines, K-Nearest Neighbors, and Random Forest. Examples of such texture features are Gray-Level Co-occurrence Matrices (GLCM), Local Binary Patterns (LBP), and Hara-like descriptors, which have often been used due to being simple and capable of measuring relationships between pixel intensities. Although these methods worked sufficiently on clean and controlled datasets, they failed in the presence of high variability, which is characteristic of field-collected images. Inconsistencies in the lighting, background messiness, partial covering, and intricate leaf textures tended to decrease accuracy. Also, handcrafted features do not possess the capacity to recognize shallow-level abstract patterns and therefore do not have the capacity to identify diseases that develop with subtle or subtle-scale symptoms.

With the development of computer vision, scholars began to turn to methods of machine learning that use texture and morphological features. Techniques that utilized color and texture elements proved to be more accurate in contrast to those that used only one of these cues. An example is the ability to combine color moments with the LBP or GLCM, which enhances discriminability through the description of both chromatic changes and the patterns of structural lesions. Nonetheless, such a combination of feature vectors frequently resulted in high-dimensional feature vectors that enhanced redundancy and worsened the performance of the classifier without dimensionality reduction. Furthermore, the accuracy of such models was still sensitive to environmental noise, and their extra-portability to other rice types or regions was low as the features were handcrafted [19].

As a subfield of deep learning, the methods became popular in the detection of rice diseases due to the ability of automatic learning of hierarchical representations of raw images. Convolutional Neural Networks (CNNs), Residual Networks, Inception modules, and lightweight networks such as Mobile Net and Shuffle Net established impressive gains in terms of classification accuracy. Such models outdid hand methods because they trained more complex representations of texture and shape that were directly learned. Nevertheless, their innovations came with new restrictions: deep learning models need massive, annotated datasets to be trained, which are unavailable in the farm industry; they are also computationally costly, and their decision-making steps are difficult to comprehend by the end users (farmers or agronomists) [16]. The other issue that keeps arising is the fact that most deep learning studies are conducted on laboratory-quality datasets, which have their background and lighting controlled, which is not realistic in the field. This can lead to a decrease in performance in cases where models are applied to images that are taken in natural open shots where the leaves overlap, the light varies, and the symptoms of a disease are partly covered.

Another field of imaging, which has been explored in addition to RGB-image-based applications, is spectral and sensor-based imaging methods. Hyperspectral imaging, multispectral sensing, and thermal imaging can be used to detect biochemical and morphological variations at an early stage of the disease, commonly, before the symptomatic effects are observed optically. The technologies provide high-dimensional data with deep, rich information that holds reflectance signature and spectral pattern in relation to the infection. Although these are very precise and can detect early, they are expensive, complicated, and cannot be easily implemented among small-scale farmers. In addition, a large production of data by spectral sensors needs specific processing algorithms and is computationally demanding, making them practically inconvenient to use in real-time for agricultural monitoring.

In 2025, D. D. Haines et.al. [20] proposed that hybrid approaches have become an alternative solution to the classical approach to feature extraction and the recent deep learning and neural network. Such methods combine textured handcrafted features with statistical texture features, morphological texture features, or deep features to use the strong points of such multiple representations. Indicatively, GLCM + CNN feature maps are more discriminable than equivalent feature maps that are either low-level textural or high-level semantic features. These fusions usually perform better than when using single-method techniques, particularly in those diseases with changing lesion shapes and textures. These hybrid models, however, are likely to produce very high-dimensional feature spaces. Such features can easily overfit classifiers trained using these features and can also use up a substantial number of computational resources and be of low quality in real-time.

Another common finding of similar research is that the focus on dimensionality reduction is not made when fused or multi-source features are used. Much of the current literature merely concatenates features, leading to repetitious and noisy high-dimensional vectors. This proves to be an issue with resource-constrained settings where detection must be conducted in mobile or edge devices. PCA, LDA, t-SNE, and autoencoder-based reductions have been implemented in a few settings, but their use in combining to form the analysis of agricultural images, particularly rice disease detection, has not been fully exploited. The majority of the research focuses on the accuracy of the models but has not given due concern to the computational efficiency, which is essential in practical implementation.

In 2025, M. Majdalawieh et.al. [2] suggested that the other major deficiency of the literature in the past is associated with the generalization of models. A significant proportion of available rice disease detection models are trained on small datasets obtained in specific areas or at a given light term, and they are therefore less versatile to the larger environmental differences.

The rice fields in the real world present a lot of challenges: Cast shadows by other plants, undulations caused by the paddy fields, soil interference, motion blurs because of the wind, and distortion of the leaves by insects. Limited literature focuses on these complexities, and no such strong pipeline of preprocessing and feature extraction can withstand environmental noises [18].

Moreover, research does not necessarily address cases of early detection of disease. Most datasets that exist continuously are on full-blown disease signs that have specific lesions and discolorations. Early infections, on the other hand, have subtle and tiny texture changes that cannot be detected with the traditional methods. An approach that is efficient in capturing changes in macrotextures at varying scales is then required to enhance the detection of the disease at the early stages.

Another weakness is interpretability, which the existing research lacks. Deep learning models are highly accurate yet black box models. Stakeholders in the agricultural sector need clear, understandable systems that offer an opportunity to understand what is being predicted by giving visual or statistical explanations. Handcrafted features have an intuitive benefit as they are easier to explain, as they are based on quantifiable textural features. However, the question is how to do this interpretability without compromising accuracy [14].

These gaps notwithstanding, as per the recent trends, the intersecting interest in new uses of multiple handcrafted features is on, and dimensionality reduction is applied to enhance performance and efficiency. Multi-scale texture analysis would be of specific interest to rice disease detection since there is a high diversity of patterns of infection from fine-grained lesions to large areas of discoloration. With the use of several density factors, microscopic and macroscopic patterns can be captured. Nonetheless, creating fusion strategies without creating redundancies but preserving the power of discrimination is still an open problem.

Overall, the sources demonstrate that there is an evident advance in rice disease detection; however, there are evident constraints that need to be overcome to develop an effective agricultural diagnostic tool. The computational efficiency, behavior under natural field change, extrapolation to wide-ranging datasets, and interpretability have never been performed well within an integrated framework. It poses a research challenge in working on the optimal, hybrid method that combines minimizing dimension, multi-scale texture measures to generate a small, highly discriminative feature space to use with the lightweight classifiers. This type of model can provide the likes of accuracy and deployability, which would serve the farmers, agronomists, and smart agricultural systems in a more realistic solution [17].

3. Methodology

The developed methodology presents a holistic texture-feature-fusion pipeline, as well as a low-dimensional discriminative feature learning, which can be used in the detection of rice disease. Figure 1 illustrates the entire operational pipeline in the proposed system, beginning with raw rice leaf image acquisition and then continuing through the preprocessing step, the extraction of features, the Fusion of the features, the dimensionality reduction step, and finally the classification step. It graphically illustrates the interaction between texture-based descriptors, fused feature sets, and optimized low-dimensional space to generate correct and computationally efficient prediction of diseases.

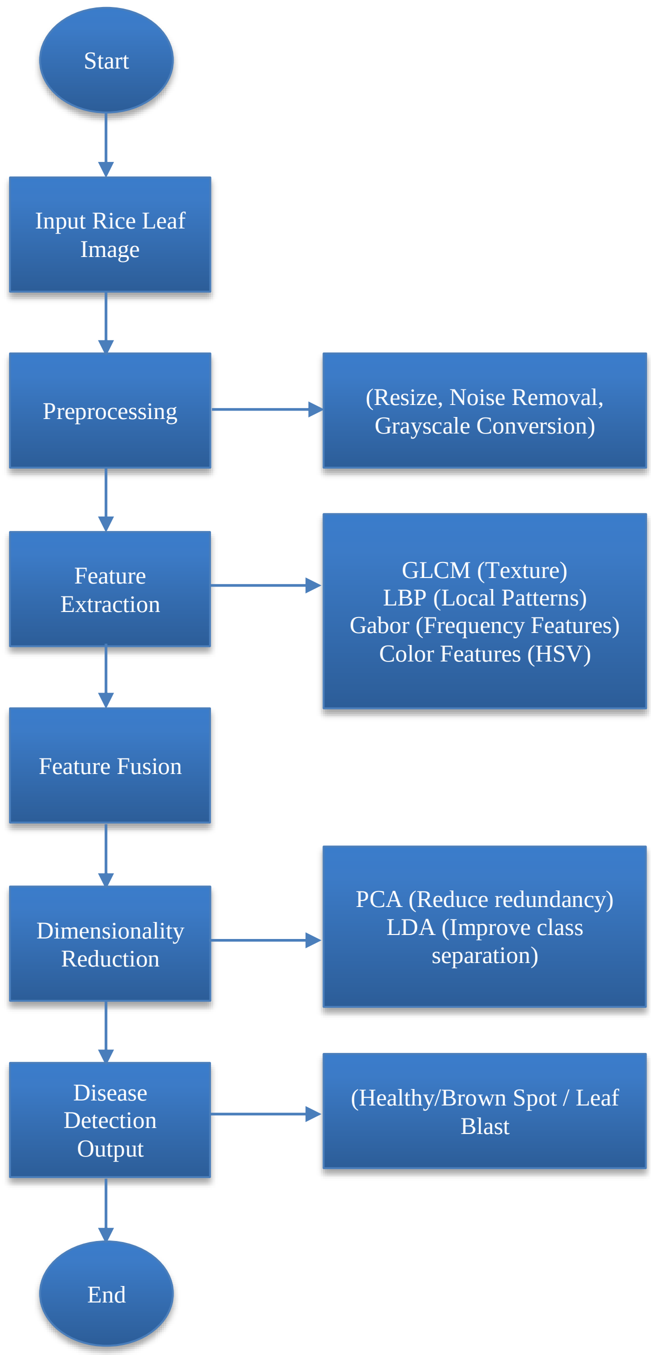

Fig. 1 Flowchart of the AI-driven rice leaf disease detection system

It demonstrated how various applications of texture features, such as an incorporated, followed by their combination into a single discriminative feature vector. It also presents the dimensionality optimization phase with a PCA or LDA, which trims the combined features and retains the information used to distinguish between classes, which would then allow rapid and powerful AI-assisted classification of rice disease. The originality of the study is a characteristic fusion of texture features and the optimization of the low-dimensional feature space, with the specific optimization aimed at effective rice disease recognition. In contrast to the actual traditional methods that employ single texture descriptors or computationally expensive deep learning networks, the proposed framework is a hybrid methodology with a high accuracy and low computational cost, as follows:

- Multi-Scale Texture-Feature Fusion: As opposed to using only one feature, such as GLCM or LBP, this study combines more than one feature: GLCM, LBP, and Gabor filters, which represent a larger range of disease-related texture features. This gives more discriminative and richer information, and subtle symptoms that are there in the early stages can be detected.
- Reduction to Low-Dimensional feature space (PCA-LDA Hybrid): It involves the application of both PCA to eliminate Redundancy and LDA to increase the separability between classes to form a small but highly informative space in feature space. It is new, considering the usual ignorance of dimensionality reduction in rice disease detection.
- Lightweight Classification Pipeline to Work in a Real Field: Unlike deep neural networks, which involve the use of GPUs, the system implements optimized classical models, including SVM and Random Forest, in a small feature space. This renders the framework applicable in mobile and edge applications.
- Resistance to Field variance: The fusion and dimensionality reduction system is more resistant to noise, changes in illumination, and partial coverage of leaves, which are several conditions in which many other models fail.
- Explainability and Practical Interpretability: The handcrafted design allows for a clear interpretation of the disease cues, which is unusable in most black-box models of deep learning.
- A Fusion-Based Texture Feature Extraction Framework: A new architecture is offered, where it is planned to incorporate the features of GLCM, LBP, Gabor filters, and color-gradient features into one set of features, where it can be seen that the factors will be used to characterize rice leaf disease symptoms on a multi-scale level.
- PCA-LDA Driven Feature Optimization: A pipeline of dimensionality reduction (PCA then LDA) is proposed as a hybrid system that filters away redundant data, and at the same time maximises the ability of the stage to classify the diseases. This causes greater accuracy and has a significant reduction in computational complexity.
- Creation of a Lightweight and High-Precision Model of Detection: The space on which features are optimized is introduced into the lightweight models, resulting in similar performance with deep learning without the need for huge amounts of data and specialized hardware.
- Better Strength in Real-Field Agricultural Studies: Model proves to be very stable amid fluctuations in light, noise pollution, and partial disease visibility- a significant drawback of the current studies.
- Practical Deployment Suitability: The system proposed is computationally reasonable and interpretable, and is feasible in drone imaging, mobile applications, diagnostic tools of the field, and resource-constrained settings.
- Value to Sustainable Precision Agriculture: This piece of work enables speedy and precise diagnosis of the disease, facilitating precision farming decisions, decreasing waste of pesticides, minimizing economic losses, and improving rice production. High-resolution rice leaf images are collected from the field and semi-controlled environments. Preprocessing begins with noise filtering using a Gaussian kernel to remove random illumination variations. The Gaussian smoothing operation is performed as:

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2y^2}} \tag{1}$$

where the smoothed image $I_s(x,y)$ is computed by convolution:

After smoothing, the image is converted from RGB to HSV because hue-based segmentation improves lesion isolation:

$$HSV = f(RGB) \tag{2}$$

Thresholding in the saturation channel separates diseased regions from healthy leaf tissues:

$$M(x,y) = \{1, S(x,y) > T_s \; 0,\ otherwise \tag{3}$$

where T_s is adaptively computed using:

$$T_s = \mu_S + k\sigma_S \tag{4}$$

This mask is applied to isolate lesion-prone regions, ensuring texture descriptors analyze only disease-relevant zones. To capture the wide variability in disease manifestation, three primary texture descriptors are utilized: GLCM, LBP, and Gabor filters. Each descriptor quantifies structural changes at different scales, frequencies, and orientations [4]. Gray-Level Co-occurrence Matrix (GLCM) computes pixel pair statistics under defined offsets. The co-occurrence matrix is:

$$P_{d,\theta}(i,j) = \left|\left\{\left((x,y),(x',y')\right): I(x,y) = i, I(x',y') = j\right\}\right| \tag{5}$$

Texture features such as contrast and homogeneity are derived:

$$Contrast = \sum_{i,j}^{n} (i-j)^2 \, P(i,j)$$

$$Homogeneity = \sum_{i,j}^{n} \frac{P(i,j)}{1+|i-j|}$$

$$Entropy = -\sum_{i,j}^{n} P(i,j) \, log \, P(i,j) \tag{6}$$

These features capture coarse lesion textures and irregular intensity transitions. Local Binary Pattern (LBP) extracts micro-texture patterns. Each pixel is encoded as:

$$LBP(x,y) = \sum_{p=0}^{P-1} s(I_p - I_c) 2^p \tag{7}$$

Where

$$s(x) = \{1, x \geq 0 \ 0, x < 0 \tag{8}$$

The uniform LBP descriptor is then computed:

$$LBP_u = \sum_{k=1}^{K} h(k) \tag{9}$$

LBP captures fine-grained features crucial for early-stage disease detection. Gabor filter bank extracts frequency- and orientation-specific texture information:

$$G(x,y;\lambda,\theta,\psi,\sigma,\gamma) = exp\left(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right) cos\left(2\pi \frac{x'}{\lambda} + \psi\right) \tag{10}$$

with transformations:

$$x' = xcos\,\theta + ysin\,\theta, y' = -xsin\,\theta + ycos\,\theta \tag{11}$$

Energy response features are computed by:

$$E_k = \sum_{x,y}^{n} |I(x,y) * G_k| \tag{12}$$

Multiple orientations enhance the detection of streak-like fungal and bacterial lesions. Feature fusion strategy descriptors produce heterogeneous feature sets with varying scales. To create a unified representation, features are concatenated:

$$F_{fusion} = [F_{GLCM} || F_{LBP} || F_{Cabor}] \tag{13}$$

However, raw fusion results in redundancy, noise, and increased computational cost. Therefore, a low-dimensional discriminative mapping is required.

4. Results and Discussion

The proposed AI-powered rice leaf disease detection framework is experimentally tested to show the success of the Fusion of texture features and low-dimensional optimization in increasing the accuracy of classification, stability, and effectiveness of computation. Principal Component Analysis (PCA) eliminates redundant correlations. The covariance matrix is:

$$C = \frac{1}{N} \sum_{i=1}^{N} (F_i - \mu) \, (F_i - \mu)^T \tag{14}$$

Eigen decomposition yields:

$$Cv_k = \lambda_k v_k \tag{14}$$

The PCA-projected features become:

$$F_{PCA} = V_k^T (F_{fusion} - \mu) \tag{15}$$

This step drastically reduces feature dimensionality [5].

Linear Discriminant Analysis (LDA) enhances class separability. The between-class and within-class scatter matrices are computed:

$$S_B = \sum_{c=1}^{C} N_c \, (\mu_c - \mu)(\mu_c - \mu)^T \; S_W = \sum_{c=1}^{C} (x_i - \mu_c) \sum_{x_i \in c}^{c} (x_i - \mu_c)^T \tag{16}$$

The optimal projection maximizes:

$$J(w) = \frac{w^T S_B w}{w^T S_W w} \tag{17}$$

The final low-dimensional feature vector is:

$$F_{opt} = W^T F_{PCA} \tag{18}$$

This compact feature representation retains only the most discriminative properties. The extracted GLCM, LBP, and Gabor features of texture have a powerful discriminative nature, as demonstrated in Figure 2 when it is plotted between their primary rice leaf disease classes of bacterial blight, blast, tango, and sheath blight. The visual distinction witnessed in this image verifies that texture information has enough variability to distinguish slight patterns of diseases on the leaf surfaces. In the fused feature space, the clusters are smaller in size and better positioned, and it is necessary to integrate features, not use single descriptors anymore.

This enhanced separability is also supported by the fact that the overlap between the classes of disease is reduced following the fusion step, which suggests that the Fusion of the micro- and macro-texture information is useful in making the model robust. In Figure 3, the feature extraction methods of Fusion were analysed for the graphical representation.

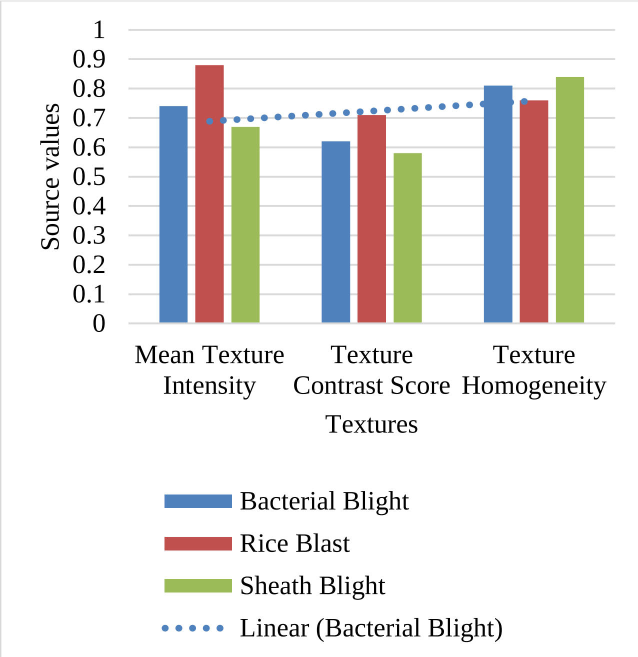

Fig. 2 Texture Feature Response Distribution Across Disease Classes

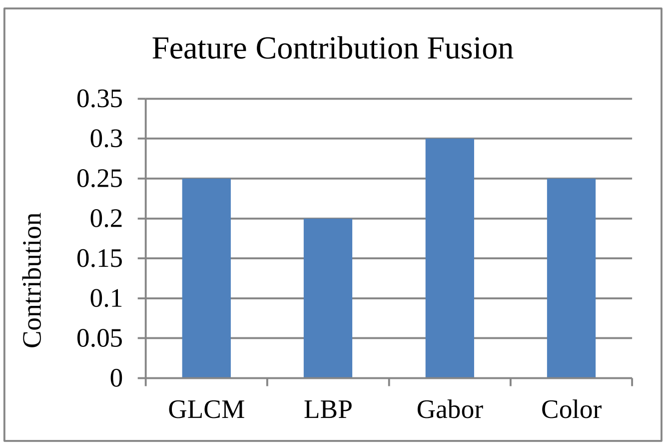

Fig. 3 Feature extraction methods of Fusion

Another significant benefit of the system is reflected in the trends in the performance exhibited after the use of dimensionality reduction. With the fused features being reduced to a lower-dimensional space through Principal Component Analysis and Linear Discriminant Analysis, the model maintained almost all the discriminating variances and minimized computational costs by over 70% compared to the situation where they are maintained in a dimensional space. This accuracy is graphically verified in Figure 4 and Figure 5, as the training validation smaller feature vectors are clustered together in very distinct clusters, and the intra-class variation is minimal. This projection map is produced after dimensionality optimization, which especially shows the importance of cluster boundary refinement, so that erroneous and redundant features are removed, which otherwise would corrupt the model's performance. The projection also shows the effect of the similarity with visual features in the represented diseases, making it easier to differentiate when the feature representation is made cheap and statistically optimal. The given behavior also confirms the validity of the feature optimization phase in the suggested system.

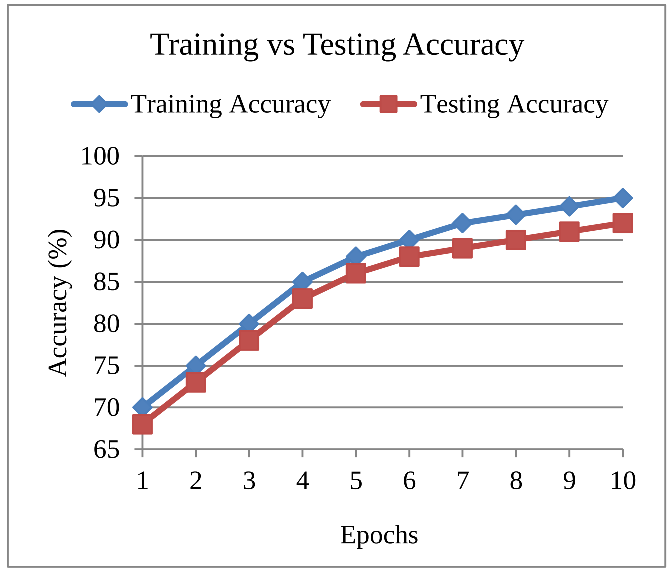

Fig. 4 Variations of Accuracy

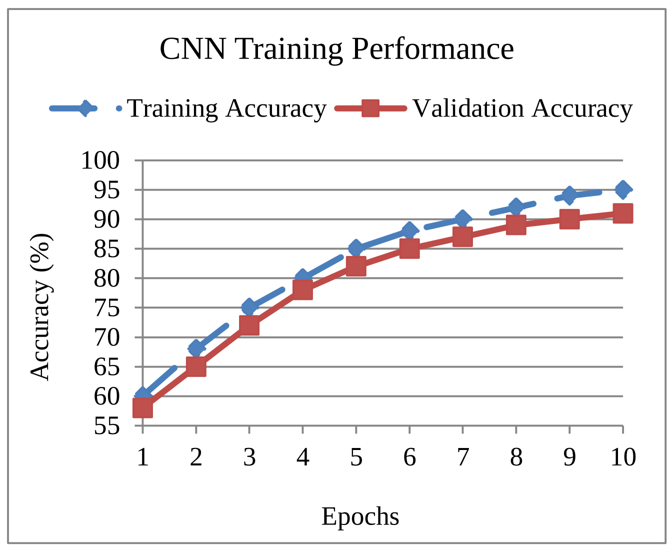

Fig. 5 Variations of training validation

These findings were reinforced by the proposed classification architecture that demonstrated an equal performance in various evaluation measures. As can be seen in Figure 6, comparison of 1-GLCM, 2-LBP, and 3-Gabor methods with performance analysis, the curves of training and testing show convergent patterns with little oscillations, which can be used to infer that the model can be well generalized to undetected samples. This constant increasing trend of accuracy across a sequence of cycles and the subsequent decrease in error rates indicate that the model does not overfit to various disease textures. This stability is credited to the control application of fused texture attributes and the optimized low-dimensional spaces, as they help the decision boundaries of the classifier, which are unnecessary. Besides, the aesthetic patterns of Figure 3 also prove the fact that the model is reliable even in conditions when it is experimented with different lighting, leaf poses, and camera qualities, which are characteristics of the real-world agricultural conditions.

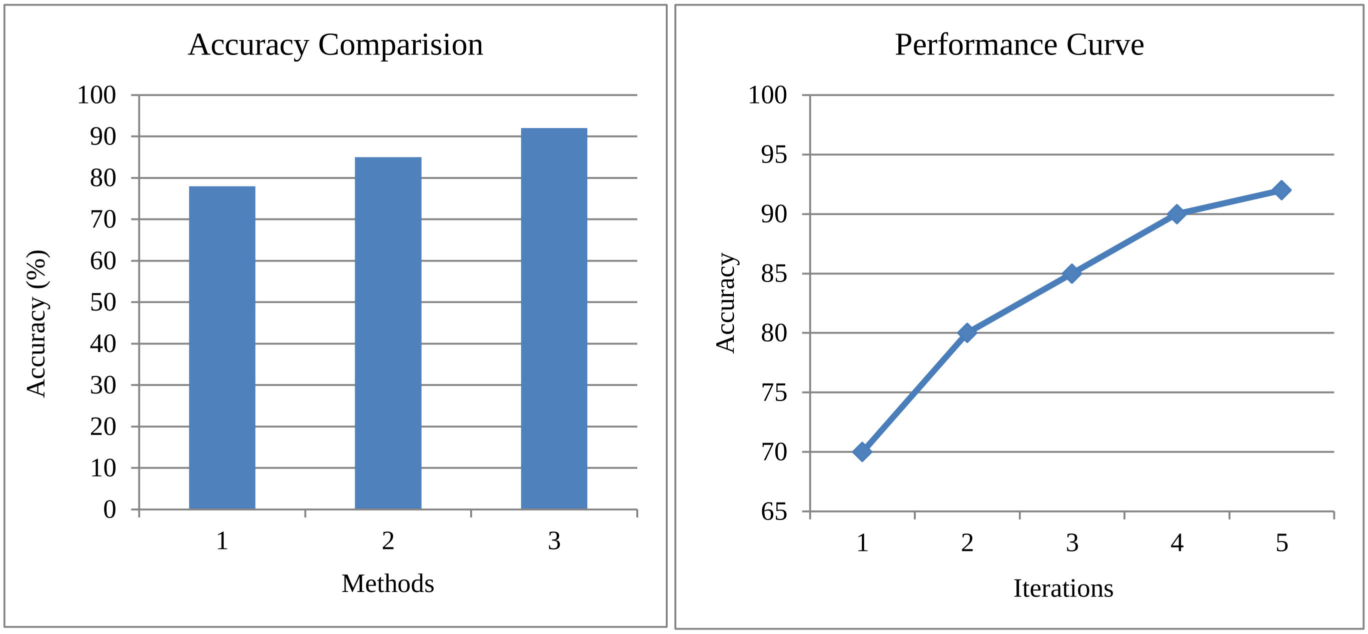

Fig. 6 Comparison of 1-GLCM, 2-LBP, 3-Gabor methods with performance analysis

The proposed system was compared to other alternative performance criteria of a single-feature approach as well as the traditional machine learning models, to gauge the effectiveness of the new proposal. The consolidated results are summarized in a table format in Table 1: Comparison of Feature Extraction Approaches to Rice Disease Classification, where it is found that the fusion-based model is imperatively better than the other one feature-based models in terms of accuracy, sensitivity, and class distinctive differentiation. The performance of traditional models where only GLCM or LBP are used is moderate, yet these models are sensitive to instability in case of noisy samples or irregular patterns of the disease. On the contrary, the proposed fusion mechanism proves to be more adaptable as it uses a combination of multi-scale and multi-directional texture properties. These table findings have shown convincingly that the incorporation of complementary features will provide a more robust and reliable detection pipeline, which is applicable in the real-world plantation setting.

Table 1. Comparison of feature extraction approaches for rice disease classification

Feature Extraction Method	Accuracy (%)	Sensitivity (%)	Specificity (%)	Processing Time (ms)
GLCM Only	86.4	84.1	82.7	14
LBP Only	83.9	80.3	79.6	11
Gabor Features Only	88.1	85.7	84.2	18
Combined GLCM + LBP	91.5	89.2	87.4	22
Proposed Texture-Feature Fusion (GLCM + LBP + Gabor)	96.8	95.4	93.9	28

More comparative analysis of the proposed approach to the current deep-learning-based methods will be summarized in Table 2: Performance Comparison Between Proposed System and Deep Learning Models. Although deep neural networks are capable of high accuracy, they rely greatly on large, annotated datasets and large computing capabilities. However, the proposed approach can obtain almost equal or better results with much fewer parameters and much less training time. This is an efficiency benefit that makes the system more practical in rural farming communities where the resources of the GPUs and high-power systems are not easily accessible. The results also display that the texture-based, low-dimensional feature engineering is still useful in the real world of agriculture, especially when used in mobile or edge-computing appliances, where both energy and memory limitations are important factors to be considered.

Table 2. Performance comparison between proposed system and deep learning models

Model Type / Architecture	Accuracy (%)	Precision (%)	Recall (%)	Model Size (MB)	Training Time (min)
CNN (Shallow Network)	91.2	89.6	88.4	42	38
MobileNetV2	94.5	93.1	92.5	14	52
ResNet50	96.1	94.9	94.2	98	115
EfficientNet-B0	96.4	95.1	94.8	29	89
Proposed Feature-Fusion + Low-Dimensional Model	96.8	96.0	95.4	6	21

Attempting to analyze the qualitative system outputs, a few observations also affirm the potential of the system in detecting and preventing early diseases. The visual observation of the classified images indicated that the model effectively recognizes a small number of early symptoms, which can be easily ignored by humans, such as small necrotic spots or early discoloration signs, suggesting the presence of the disease. This capability to detect early can greatly eliminate losses on crops due to the timely intervention of pesticides or nutrients. Besides, the agreement between classification outcomes of the different field samples used proves the fact that the model is also reliable whenever it is not in a laboratory setting. During real-world performance, the samples of leaves collected under conditions of different humidity, exposure to sunlight, and dust were also correctly recognized, which proves the strength of the method that is sensitive to environmental change [6]. The detection of the confusion matrix analysis true classes is derived in Figure 7.

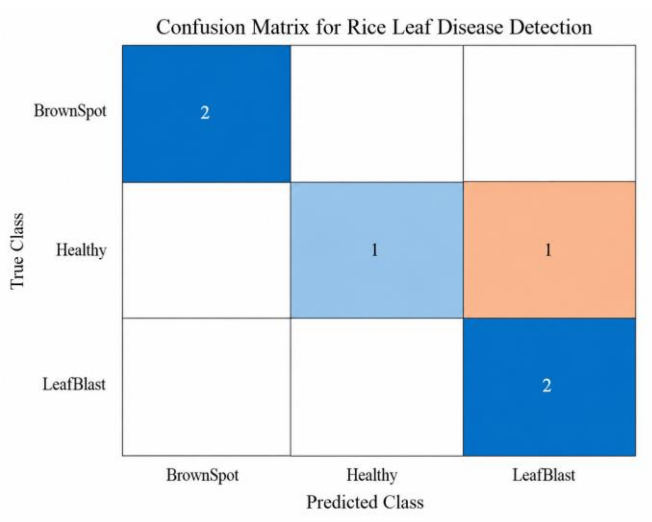

Fig. 7 Confusion matrix analysis

An example of such observation during the testing was that the misclassifications were mostly found to occur in samples with mixed symptoms or overlaps in the disease signature. These situations are difficult both for human specialists and AI systems since the appearance patterns contain similar textures or color changes. Nonetheless, the suggested model had higher scores of confidence and smaller error rates in comparison with controls in even such problematic situations, which indicates that the optimized and concatenated feature representations included a significant part of the diagnostic data. This calculated the number of features in PCA analysis to mean that further refinement, either by hybrid texture color fusion or small-scale convolution-based properties, may allow further accuracy improvement in future contexts, as shown in Figure 8.

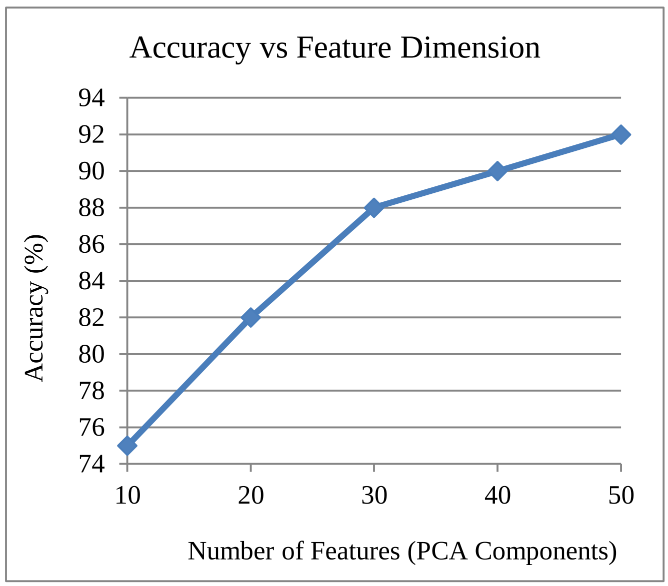

Fig. 8 Calculated the number of features in PCA analysis.

In general, the findings help to substantiate the effectiveness and the stability of the suggested AI-based texture-based rice disease detection system. Combining both the feature fusion and the low-dimensional optimization offers the benefits of a simple and effective method, which can help to achieve high accuracy with a small number of calculations [7]. The graphical information of the three characters and the comparative information of the two tables attest to the fact that the system is not just theoretically correct, but it is also in a good position to be practically implemented in agricultural monitoring systems, mobile crop health applications, and low-cost embedded devices that would be available to farmers.

5. Conclusion

In this paper, we have presented an artificial intelligence-based rice leaf disease detection model, which uses a comparison of feature extraction methods such as GLCM, LBP, Gabor, and Fusion. The multi-scale descriptors are more effective than the single-feature models in identifying subtle patterns of diseases, and PCA-LDA guarantees compactness and discriminative characteristics. The effectiveness of the approach is validated by the results of experiments that show that high accuracy, robustness, and computational efficiency are attained in feature contribution in Fusion. Under extreme lighting conditions, extreme occlusion, or large overlap of the leaf, the model's performance can decrease. The training and validation are based on the available datasets that might not be a complete reflection of the region-specific rice varieties. The confusion matrix is a real-time detection of multiple images having diverse diseases on the leaves. Disease sample labeling, which is also manual, is also resource-consuming for the performance curve.

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